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A Framework of Automation Use

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Abstract

Although dramatic increases in the use of automation in recent years have occurred across society, research has found that human operators often under-use (disuse) and overly rely on (misuse) automated aids (Parasuraman & Riley, 1997). A general framework of automation use, which proposes that cognitive, social, and motivational processes may lead to productivity loss of human-computer teams, is developed, described, and defended with anecdotal and experimental findings. More specifically, automation use is predicted to be affected by the difference between the reliability of the automated aid and the reliability of manual operation, task difficulty, the number of tasks, interest in the task, fatigue, cognitive overhead, the rewards for successful performance, the penalties for unsuccessful performance, and several cognitive biases. Suggestions for future research are briefly discussed.

Contents

1. **Disuse** 2

2. **Misuse** 2

3. **Framework of Automation Use** 3
   3.1 Cognitive Processes: Cognitive Miser Hypothesis - Automation Bias 3
   3.2 Social Processes: Authority Hypothesis - Trust in Automation . 7
   3.3 Motivational Processes: Diffusion of Responsibility 12

References 21

Distribution List 27

Report Documentation Page 31

Figures

1. Automation Bias 4
2. Sample Slide Showing Soldier 5
3. Relative Trust 9
4. Social Processes 12
5. Expectancy 13
6. Costs 15
7. Importance of Outcome 16
8. Framework of Automation Use 18

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A FRAMEWORK OF AUTOMATION USE

In December 1995, the crew of an American Airlines Boeing 757, descending through a mountain valley toward Cali, Columbia, attempted to route the aircraft toward their destination by entering into the flight management system (FMS) a substring of the code for a Cali navigational beacon. The computer's stored database of navigational beacons contained two very similar codes. One code denoted the beacon near Cali, which was several dozen miles ahead of the airplane. The other code corresponded to a beacon at the Bogota airport, several dozen miles behind the airplane. Presented by the FMS with a list of nearby beacons matching the entered substring, the crew initiated an overlearned behavior and selected the computer's first presented alternative; unfortunately, the FMS had presented the Bogota beacon first. The flight management computer dutifully began turning the aircraft toward Bogota. Shortly after this, the aircraft crashed into the side of a mountain, killing all on board (Phillips, 1999).

Information technology is changing the nature of work. Access to more relevant, accurate, and timely information than was previously possible has drastically increased the use of automation across society, including the military (Cesar, 1995). The requirement for automation is highlighted by the increasing complexity of the military mission, which is expanding to include the full spectrum of conflict, from humanitarian assistance and peace keeping to small-scale contingencies and major wars. To enhance situational awareness and a myriad of other tasks, the military decision maker is often provided with automated aids. The underlying assumption in providing these automated aids to military personnel is that the human-computer "team" will be more productive than either the human or the automated aid would be working alone. Some researchers have found support for this underlying assumption (Corcoran, Dennett, & Carpenter, 1972; Dalal & Kasper, 1994; Parasuraman, 1987; Thackray & Touchstone, 1989a). However, as the previous vignette illustrates, human-computer teams do not always function optimally.

One strategy used to optimize human-computer performance has been to ask system designers to create automated aids that are increasingly more reliable. Increasing the automated aid's reliability is assumed to lead to increased human-computer "team" performance. As with human teams, however, increasing the reliability of one team member's performance will not necessarily affect the team's performance. Sorkin and Woods' (1985) signal detection analysis revealed that optimizing an automated aid's performance would not always optimize the human-computer team's performance of a monitoring task. Specifically, they found that using a response criterion that yielded the best performance for the automated aid (i.e., highest detection rates and fewest false alarms) did not yield the best performance for the human-automated team. Although "synergy" can be found in human-computer teams (e.g., Dalal & Kasper, 1994), it is not likely to be gained by optimizing human-alone or computer-alone performances. The interaction between the automated aid and human operator must be considered.

By understanding the processes that human operators use when deciding to rely on their decisions or on an automated aid's decisions, one may be able to better design systems and train military decision makers about the appropriate use of automated aids. The purpose of this report is to present a general framework we believe will be useful in guiding research to understand human operators' task allocation decisions.

1. Disuse

A rational decision maker will rely on an automated aid when doing so will maximize gains and/or minimize losses. Failure to rely on an aid in this situation constitutes disuse (Parasuraman & Riley, 1997). Disuse is defined as "underutilization of automation" (p. 233). Anecdotal evidence supports disuse; Parasuraman and Riley (1997) described many real-world incidences in which disastrous results occurred because people ignored automated warning signals. Further, laboratory experiments have found disuse in paradigms in which the aid's decisions are provided only after the human operators have indicated their decision (Dzindolet, Pierce, Beck, & Dawe, 1999; Moes, Knox, Pierce, & Beck, 1999). For example, Moes and others (1999) found that most college students (67%) chose to ignore the decisions of an automated aid even after being provided with feedback that their automated aid made half as many errors as they did during 200 prior trials. In addition, Riley (1996) found that students favored manual operation over automated control, even when doing so was clearly not an optimal strategy.

2. Misuse

When ignoring an automated aid will maximize gains and/or minimize losses, the rational decision maker will ignore the aid and rely on his or her decisions. Relying on the automated aid in this circumstance would constitute misuse (Parasuraman & Riley, 1997). Misuse is defined as "over-reliance on automation" (p. 233). Parasuraman, Molloy and Singh (1993) and Singh, Molloy, and Parasuraman (1997) found misuse among operators performing monitoring functions. They labeled this behavior complacency, "a psychological state characterized by a low index of suspicion" (Wiener, 1981, p. 809). Misuse has also been found with automated decision aids (Dzindolet, Pierce, Beck, Dawe, & Anderson, to be published; Layton, Smith, & McCoy, 1994; Mosier & Skitka, 1996).

3. Framework of Automation Use

What are the processes leading to appropriate use, misuse, and disuse of an automated aid? Mosier and Skitka (1996) outlined three possible reasons (hypotheses) why people inappropriately use automation: (1) cognitive miser, (2) authority, and (3) diffusion of responsibility. These three hypotheses parallel three processes: cognitive, social, and motivational, which have been implicated as the causes of productivity loss found in groups (e.g., Mullen, Johnson, & Salas, 1991). Since many researchers have considered a human-computer "team" to be a group in which one member happens not to be human (e.g., Bowers, Oser, Salas, & Cannon-Bowers, 1996), we hypothesize that these same three processes can lead to sub-optimal performance in human-computer teams. The framework of automation use hypothesizes that cognitive, social, and motivational processes of the human operator combine to predict automation use. A discussion of each process as it relates to inappropriate use is presented in the next three sections.

3.1 Cognitive Processes: Cognitive Miser Hypothesis - Automation Bias

Mosier and Skitka (1996) hypothesized that people may overly rely on automated systems when making decisions because of faulty cognitive processing. In addition to the large body of literature examining errors attributable to flawed cognitive processing in *individual* decision making (Tversky & Kahneman, 1973), the social cognition literature is replete with examples of less-than-ideal cognitive processing while people work in teams or groups. Errors and biases have been identified in various domains of social psychology (e.g., illusory correlation, "in-group" differentiation, and "out-group" homogeneity in stereotype formation [Hamilton & Sherman, 1989; Mullen & Hu, 1989], the halo effect and the negativity bias in impression formation [Skowronski & Carlston, 1989], the confirmation bias and self-handicapping in attribution [Arkin & Baumgardner, 1985; Leyens & Yzerbyt, 1992]). People often adopt effort-saving strategies called "heuristics" instead of logically processing relevant pieces of information. Mosier and Skitka (1996, p. 205) coined the term "automation bias" to refer to "the tendency to use automated cues as a heuristic replacement for vigilant information seeking and processing."

The fact that the automated system provides a decision may lead the decision maker to rely on this information in a heuristic manner (see Figure 1). Rather than going through the cognitive effort of gathering and processing information, the decision maker uses information supplied by the automated systems (Mosier & Skitka, 1996). Conceivably, this may occur in various degrees. In its most extreme form, the decision reached by the automated aid is immediately adopted. In a less extreme form, the decision reached by the aid may be given an inappropriately large role in the human's decision-making process. For example,

Layton, Smith, and McCoy (1994) found that many pilots provided with an automated aid's poor en-route flight plan did not explore other solutions (e.g., they did not generate actual flight plans on screen) as much as pilots who were not provided with the automated aid's decision.

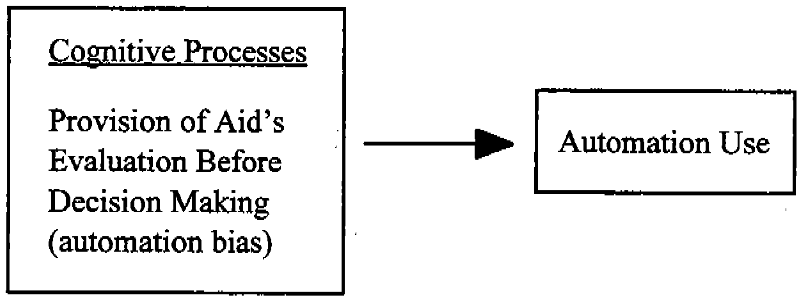

Figure 1. Automation Bias.

The automation bias will lead participants to rely on the automated aid. Often, this strategy will be appropriate. However, during certain conditions, this reliance may be inappropriate, leading to misuse.

Although the automation bias plays a role in predicting automation use, it cannot account for the full range of potential findings. Specifically, automation bias would not be able to account for the anecdotal evidence for disuse when an automated aid's evaluation is provided to humans before they report a final decision. The information received from the automated aid is predicted to influence the human's response. The human operator is not predicted to ignore information provided by the automated aid.

Indirect evidence to support the existence of automation bias can be found by examining task allocation decisions across two studies with similar procedures (Dzindolet et al., to be published; Dzindolet et al., 1999).

Participants viewed about 200 slides displaying pictures of Fort Sill terrain on a computer screen (see Figure 2 for a sample slide). About half of the slides contained one soldier ("target") in various levels of camouflage; the remaining slides were of terrain only.

Sometimes, the target was easy to detect (as in Figure 2); other times, it was more difficult to find. Each slide was presented on the computer screen for about 3/4 of a second. In the experiment by Dzindolet and others (to be published), participants were provided with the absent or present evaluation of an automated aid known to be accurate 60%, 75%, or 90% of the time (based on the condition to which the participant was randomly assigned). Specifically, participants were told that a computer routine had been written to assist them in performing their task. They were told that the routine performed a rapid scan of

the photograph and looked for contrasts that suggested the presence of a human being. If the contrast detector routine determined the soldier was probably present, the word "present" and a red circle appeared. If the contrast detector routine determined the soldier was probably absent, the word "absent" and a green circle appeared.

Figure 2. Sample Slide Showing Soldier.

The next screen asked the students to indicate whether they believed the soldier was in the slide. They were told that they had as much time as they needed to make their decision. Participants were informed that there were two types of errors that could be made. One error was made when they indicated that the soldier was present when he was not. The other error was made when they indicated that the soldier was not present when he actually was. Participants were told that both errors were equally serious and that they should attempt to avoid them.

Finally, the participants were asked to indicate the extent to which they were certain their decision was correct. A five-point Likert scale ranging from "highly confident" to "not at all confident" was provided.

Analyzed with principles from signal detection theory, the error rate was determined to be the complement of the area under the receiver operator curve. To examine misuse and disuse, the probability of error was determined for two subsets of the data. Misuse, or over-reliance on the contrast detector, was operationally defined as the $\underline{p}$(error | aid error). Disuse, or underutilization of

the contrast detector, was operationally defined as the p(error | aid correct). Analyses indicated that regardless of the reliability of the automated aid, each participant was more likely to err by relying on his decision aid than by ignoring it, p(error | aid error) = .27; p(error | aid correct) = .13.

Therefore, when provided with the aid's decisions first, thereby allowing the automation bias to occur, participants were more likely to misuse than disuse their automated aids.

However, in the studies by Dzindolet and others (1999), the automation bias was eliminated. Participants were *not* provided with the decisions reached by the contrast detector until *after* they had indicated their decision and their level of confidence in their decision. Without the automation bias, would participants still be more likely to misuse than disuse their automated aids?

Participants in these studies viewed the slide of Fort Sill terrain for about 3/4 of a second, indicated their decision, rated their confidence, and only then were provided with the contrast detector's decision. When they completed all 200 slides, some participants were told the number of errors they and their aid made. Finally, students were told they could earn $0.50 in coupons to be used at the cafeteria in the student union for every correct decision made in ten randomly chosen trials. Participants had to *choose* whether the performance would be based on ***their decisions*** or on ***the decisions of their aid.*** After making their choice, students were asked to justify their choice in writing.

Rather than misusing the contrast detector, participants in these studies disused the automated aid. Even among participants provided with feedback that their aid's performance was far superior to their own, the majority (81%) chose to rely on their own decisions rather than on the decisions of the automated aid!

Therefore, when the automation bias could play a role in the decision to rely on automation, misuse occurred more than disuse (Dzindolet et al., to be published). However, when the automation bias was eliminated by the provision of the automated aid's decisions only *after* participants recorded their decision, disuse (not misuse) was found in a subsequent task allocation decision (Dzindolet et al., 1999).

Future research should be directed at understanding the automation bias and identifying variables that affect it. The results from Dzindolet and others (to be published) imply that the reliability of the automated system does not affect the automation bias. However, in the study, the reliability information was provided to participants early in their interaction with the system. If the reliability information had been provided continually throughout the task (e.g., feedback after every trial), perhaps automation reliability would have affected the automation bias. Future research should examine this and other variables that

affect the automation bias in an effort to reduce the bias and increase the likelihood that human operators will appropriately rely on automated systems.

Although we hypothesize that automation bias plays a role in automation use and misuse, we do not believe it is the only important variable. At the very least, processes predicting the bias toward disuse, which are described in the studies by Dzindolet and others (1999), are needed. Analyses of the justifications of the task allocation decisions provided by participants in one of the experiments by Dzindolet and others (1999) indicated that other variables might play a role. For example, nearly 1/4 (23%) of the participants justified their disuse by stating that they did not trust the automated aid as much as they trusted themselves.

3.2 Social Processes: Authority Hypothesis - Trust in Automation

A second explanation of the inappropriate use of automated aids has to do with the role of the computer as the expert. According to Mosier and Skitka's (1996) authority hypothesis, people rely on the automated system's decision because they believe it to be more reliable and thus place greater trust in it. Many other researchers have indicated that trust is one important variable in predicting automation use (Cohen, Parasuraman, & Freeman, 1998; Lee & Moray, 1992, 1994; Moray, Inagaki, & Itoh, 2000; Muir, 1987, 1994; Singh, Molloy, & Parasuraman, 1993; Tan & Lewandowsky, 1996). Overly trusting an automated aid will lead human operators to misuse; lack of trust in a superior aid will lead to disuse.

Parasuraman and Riley (1997) described many real-world incidences in which disastrous results occurred because people ignored automated warning signals they saw as untrustworthy. Ignoring automated alarm systems that have previously signaled erroneously has been dubbed the "cry wolf" effect (Bliss, 1997; Bliss, Dunn, & Fuller, 1995). Publicizing the alarm's trustworthiness was one strategy that proved effective in reducing the cry wolf phenomenon (Bliss et al., 1995).

Muir (1987, 1994), one of the first researchers to focus on automation trust, relied on the literature of human trust to understand the human operator's trust of automation. She hypothesized that automation will be seen as more trustworthy if it is predictable, dependable, and inspires faith that the automated system will behave as expected in unknown situations. Trust is gained in the areas of persistence, technical competence, and fiduciary responsibility.

To test some of Muir's hypotheses, Lee and Moray (1992, 1994) examined the effect of trust in automation on task allocation decisions. Participants controlled a simulated orange juice pasteurization plant for 2 hours each day for three days. The simulation included three subsystems, each of which could be operated manually or automatically. Participants could allocate tasks any way they

wished and could change their allocations easily. As part of the experiment, whether controlled automatically or manually, one of the subsystems failed periodically. Lee and Moray (1992, 1994) were especially interested in task allocation changes after these failure events, since Muir predicted that after failure events, trust would decline rapidly and slowly increase as the system performed without making errors. At the end of each session, participants completed a questionnaire about their trust in the automation and self-confidence in performing the tasks manually.

Results indicated strong individual differences in automation use. Some participants were prone to use manual control; others were prone to use automation. Singh and others (1993) created a scale to determine individual differences in the propensity to misuse automated aids, which may have been able to predict which individuals would tend to rely on automation and which would tend to rely on manual operation.

Inconsistent with Muir's hypotheses, the Lee and Moray (1992, 1994) participants rarely changed their allocation task decisions. Once the human operator assigned a subsystem to automated or manual control, he or she was unlikely to change the decision during that session—even after failure events.

To predict trust in automation dynamically, Cohen, Parasuraman, and Freeman (1998) extended Muir's (and others) work and created an especially promising model, Argument-based Probabilistic Trust (APT). This model defines trust as the perceived probability of the system's reliability, given certain situations. Instead of trust being correlated with the predicted reliability of the system (e.g., Muir's 1994 theory), trust *is* the predicted reliability of the system.

Whether predicted reliability is related to trust (e.g., Muir, 1994) or is trust (e.g., APT model), we do not believe that predicted reliability will directly predict automation use. The predicted reliability of an automated aid is meaningful only in the context of some standard of performance. What standard did Lee and Moray's (1992, 1994) subjects use? Automation use was found to be related to subjects' estimates of the ability of the automated aid *relative to estimates of their own ability*. Thus, we hypothesize that automation use is determined from the outcome of a comparison process between the perceived reliability of the automated aid (trust in aid) and the perceived reliability of manual control (trust in self). We call the outcome of the decision process the perceived utility of the automated aid (see Figure 3). If one perceives the ability of the aid to be greater than one's own, perceived utility of the aid will be high. If one perceives the ability of the aid to be inferior to one's own, perceived utility of the aid will be low. People may misuse an automated aid because the perceived utility of the aid is overestimated; they may disuse an aid when the perceived utility of the aid is underestimated.

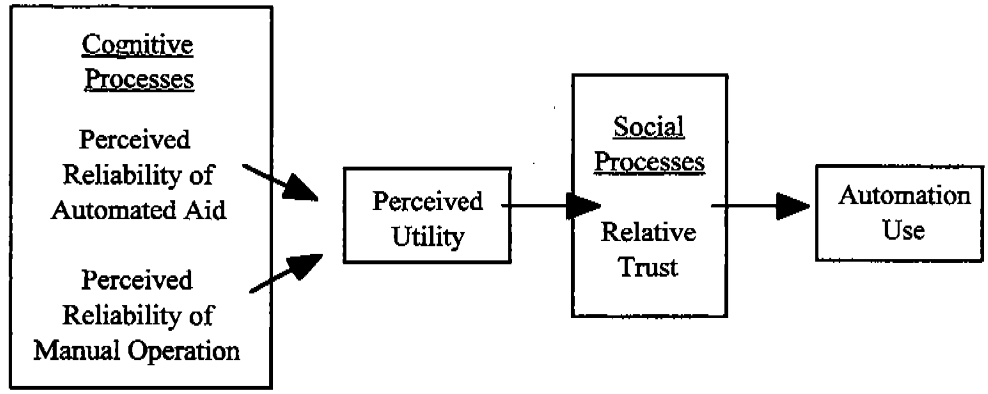

Figure 3. Relative Trust.

Since accurately perceiving the utility of the aid will lead to appropriate automation use, it is very important that we gain an understanding of how this perception is formed. The perceived utility of the aid will be most accurate when the ***actual*** ability of the aid and ***actual*** ability of the manual operator are compared. However, the "actual" ability is never known. Perceived ability is determined through a function of actual ability and error. The larger the error, the more likely misuse and disuse is to occur. We suspect that at least two types of errors occur.

One type of error occurs when human operators estimate their own performance. Human operators tend to overestimate their own ability. Social psychological literature is fraught with examples of self-serving biases. Humans exaggerate their contribution to a group product (appropriation of ideas, Wicklund, 1989), overestimate the number of tasks they can complete in a given period of time (planning fallacy, Buehler, Griffin, & Ross, 1994), are overconfident in negotiations (Neale & Bazerman, 1985), and inflate their role in positive outcomes (Whitley & Frieze, 1985). Thus, we hypothesize that human operators will be likely to overestimate their manual ability.

Providing accurate feedback will assuage the self-serving biases. Using the paradigm of Dzindolet and others (1999) described earlier, Dzindolet, Beck, and Pierce (2000) found that providing feedback of the contrast detector's superior performance after each trial and/or at the end of the 200 trials reduced disuse.

The other type of error occurs when human operators estimate the performance of their automated aid. Before working with the aid, the human must rely on stereotypes formed about the performance of automated aids. Although individual differences exist, a bias toward automation leads many people to predict nearly perfect performances from automated aids. Dzindolet and others (1999) told half the participants that they would be provided with the decisions reached by the contrast detector before they made their soldier absent or present

decision for each of 200 slides. Other participants were told that they would be provided with the decisions reached by the previous participant before making their soldier absent or present decision for each of the 200 trials. The instructions informed the participants that their aid (human or automated) was not perfect. When asked to estimate the number of errors that the automated aid would make in the imminent 200 trials, participants predicted that the aid would make an average of only 14.19 errors (i.e., correct nearly 93% of the time). When asked to estimate the number of errors that the human aid would make, participants predicted an average of 46.17 errors (i.e., correct only 77% of the time—only 27% better than chance!). Although previous researchers have reported that people tend to have negative initial expectations of automation (e.g., Halpin, Johnson, & Thornberry, 1973), our studies reveal a strong bias toward automation.[1]

In summary, the perceived reliability of the automated aid is determined by the actual reliability of the automated aid and by the bias toward automation. The perceived reliability of manual operation is determined by the actual reliability of the human operator and by self-serving biases.

We hypothesize that what is important in determining automation use, however, is not the perceived reliability of the aid or the perceived reliability of manual control but the result of a comparison process between the two: perceived utility. Increasing the reliability of the aid will not increase automation use unless the aid's perceived reliability surpasses that of manual operations.

This can explain the inconsistent findings concerning automation reliability and human-computer performance. For example, Riley (1994) and Moray, Inagaki, and Itoh (2000) found that people were more likely to overly rely on a more reliable automated system than on a less reliable one. Yet, Dzindolet and others (to be published) did not find that participants rely on more reliable decision aids than on less reliable ones.

Similarly, Parasuraman and others (1993) and Singh and others (1997) did not find reliability to affect automation use with a monitoring task. Participants were required to simultaneously perform three flight simulation tasks. Two of the tasks required manual operation, but a third task (monitoring) was automated. The automation varied in its reliability and in its variability. Some participants worked with an automated system that was consistently correct 87.5% of the time; others worked with a system that was consistently correct 56.25% of the

[1]Confusion could arise from the similarity of the term, bias toward automation, to a term discussed earlier, automation bias. Bias toward automation refers to the finding that participants initially expect automated aids to perform better than human operators (Dzindolet et al., 1999). The automation bias is a term coined by Mosier and Skitka (1996) to refer to "the tendency to use automated cues as a heuristic replacement for vigilant information seeking and processing" (p. 205). In fact, the cues (i.e., the decisions) would not have to come from an automated aid. We would expect the decisions of both human and automated aids to be relied on in a heuristic manner.

time. Others worked with machines that varied in reliability. Some students started with automated systems that were accurate 87.5% of the time for the first 10 minutes of the session of the experiment but then alternated in reliability to 56.25% and 87.5% during 10-minute intervals for the rest of the experimental session. Other participants started working with a less reliable automated system that alternated to a more reliable every 10 minutes during the experimental session.

Over-reliance on automation was found by participants in both of the constant conditions (Parasuraman et al., 1993), and the saliency of the automation failure signals did not affect the results (Singh et al., 1997). Thus, when the reliability of the automation varied, participants appropriately relied on the automated monitoring system. However, when the system was consistent in its reliability (either high or low), participants tended to overly rely on the system's monitoring capabilities. Singh and others (1997) hypothesize that complacency was attributable to the participants being too trusting of the automation. "Participants may have begun the automated sessions with an equal amount of trust in the automation. However, as the reliability of the automation fluctuated for the variable group, their trust may have declined. Therefore, the variability group may have been more skeptical of the automation and thus been more vigilant for automation failures" (p. 28).

Why did reliability not affect automation use in the studies of Parasuraman and others (1993) and Singh and others (1997)? This finding is unexpected according to the APT model and Muir's model of trust. Our model predicts that automation's reliability will affect automation use only if it leads the human operator to perceive the aid's reliability as greater than his or her own.

In summary, we hypothesize that people may misuse an automated aid when the perceived utility of the aid is overestimated and disuse an aid when the perceived utility of the aid is underestimated. The perceived utility of the system results from a comparison between the automated system's perceived ability and one's own perceived ability. Perceived ability is hypothesized to be affected by actual ability and various biases (self-serving and bias toward automation).

Reducing the biases should decrease inappropriate automation use. Dzindolet and others (to be published) found that disuse could be reduced by providing participants multiple forms of feedback of the aid's superior performance.

In addition to trust (through perceived utility) affecting automation use, we conjecture that two other social processes may affect automation use: feelings of control and moral obligation to rely on self. Figure 4 illustrates the social processes.

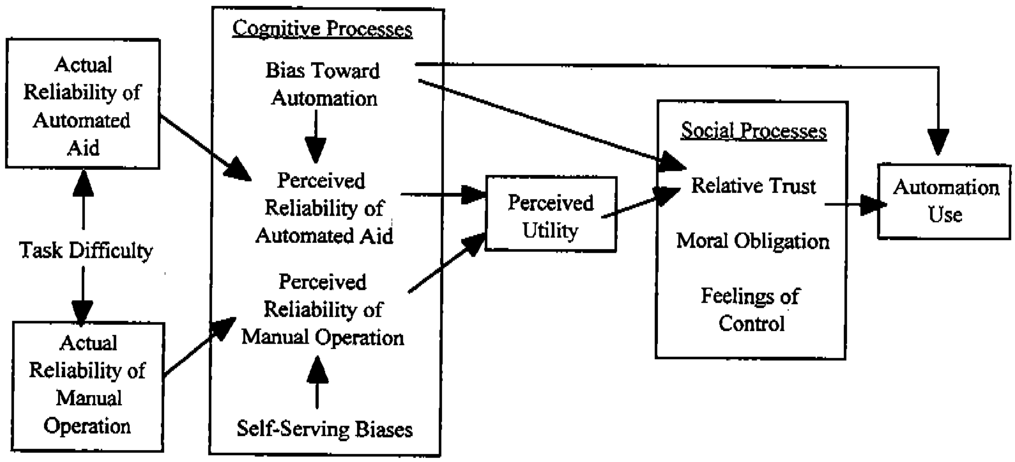

Figure 4. Social Processes.

Analyses of the justifications of the task allocation decisions provided by participants in one of the experiments by Dzindolet and others (1999) revealed that 71% of the students (who were provided cumulative feedback that indicated that the aid made about an equal number of errors as the participant) justified self-reliance with statements indicating they would not earn more rewards if they relied on the aid. Since the task allocation decision would not affect the size of their reward, why did participants choose self-reliance? We hypothesize that self-reliance provides participants with an illusion of control. Langer (1983) has found that people often behave illogically in order to have an illusion of control.

In addition, many participants (although more of whom worked with human aids [n=24, 43.64%] than automated aids [n=9, 16.67%], $\underline{X}^2 = 8.58$, $\underline{p} < .01$) justified self- reliance with statements concerning a moral obligation to rely on self. One student wrote, "I would rather the amount of coupons I receive be based on my performance; it seems more 'fair' to me." Another wrote, "I feel anything earned should be based on how well I did or didn't do."

Much research remains to be performed to explore the social processes and their effect on automation use. Only with a more clear understanding of these processes will we be able to suggest ways that misuse and disuse can be reduced.

The variables that affect perceived utility are of special interest to us because perceived utility is not only predicted to affect trust but also to affect the last of the processes, the motivational process—that is, the variables that affect automation use by increasing or decreasing the amount of effort expended on the task.

3.3 Motivational Processes: Diffusion of Responsibility

A third explanation of the over-reliance on automation discussed by Mosier and Skitka (1996) involves the idea that when people work in a group, the responsibility for the group's product is diffused among the group members. Several researchers have thought of the human-computer system as a dyad or team in which one member is not human (Bowers et al., 1996; Scerbo, 1996; Woods, 1996). Thus, the human may feel less responsible for the outcome when working with an automated system than when working without one. The person may not be as motivated to extend as much effort when paired with an automated system as when working alone. In the social psychological literature, this phenomenon has been dubbed "social loafing" (Latane, Williams, & Harkins, 1979) or "free riding" (Kerr & Bruun, 1983).

One theory that has been successful in accounting for much of the findings in the social loafing literature is Shepperd's Expectancy Value Theory (1993, 1998). According to this theory, motivation is predicted from a function of three factors: expectancy, instrumentality, and outcome value.

3.3.1 Expectancy

The first factor, expectancy, is the extent to which members feel that their efforts are necessary for the group to succeed (see Figure 5). When members feel their contributions are dispensable or when one's individual contribution is unidentifiable or not evaluated, one is likely to free ride or work less (Kerr & Bruun, 1983; Williams & Karau, 1991).

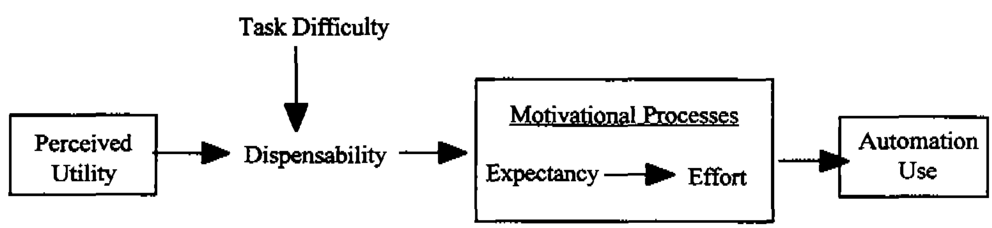

Figure 5. Expectancy.

With a human-computer system, individual contributions tend to be identifiable and evaluated; thus, these variables are not thought to affect motivational processes. However, when the perceived utility of a system is high, one is likely to feel that his or her efforts are more dispensable than when he or she is when working with a system low in perceived utility. Thus, we would expect human operators to be likely to misuse an automated system deemed more reliable than themselves in the same way people free ride on group members deemed more reliable than themselves.

Task difficulty, which is predicted to affect perceived utility (see Figure 5), has also been found to directly affect dispensability. In fact, one of the methods researchers have used to make group members feel that their efforts are indispensable has been to imply that the difficulty of the task makes the demands on each group member particularly high (Shepperd, 1993). For example, Harkins and Petty (1982) asked participants to generate as many uses as they could for either a knife (easy task) or for a detached door knob (difficult task) either alone or in nine-member groups. Although they found social loafing with the easy task (group members did not generate as many ideas as those working alone), they did not find social loafing with the difficult task.

In summary, the more dispensable the human operator is made to feel, the lower expectancy will be; effort will probably be low and the likelihood that the automated aid will be relied upon will be high. In some instances, this will lead to automation misuse.

3.3.2 Instrumentality

Instrumentality, the extent to which members feel that the group's successful performance will lead to a positive overall outcome, is also predicted to affect effort. Members who feel the outcome is not contingent on the group's performance are less likely to work hard. Thus, inappropriate use should be high among members who feel their group's performance is irrelevant. In one study, Shepperd (1998) varied instrumentality. Half the participants were told that the seven groups (of ten groups) with the highest number of ideas generated would earn a reward. Other participants were told that the members of the four groups (of 40 groups) with the highest number of ideas generated would have their names entered into a lottery. One name would be drawn and that person would earn a reward. Thus, in the former condition, members had 7 in 10 chances of attaining the reward; in the latter condition, there was only 1 in 200 chances of attaining the reward. In addition to the optimistic bias (participants estimated their chance of winning to be about 1 in 4), Shepperd found that performance suffered when instrumentality was lowered.

On the battlefield, there will be many soldier-computer teams. If the human determines that the overall outcome is not contingent on his or her human-computer team (either because he estimates other teams to be more able to do the task or that his human-computer team is dispensable), then the human will put little effort into the task.

3.3.3 Outcome Value

Finally, the value of the outcome is predicted to affect motivation. Outcome value is the difference between the importance of the outcome and the costs associated with working hard. Increasing the costs or minimizing the importance of the reward will lead members to put forth less effort. More effort will be extended toward tasks that lead to valuable outcomes without requiring much

cost. Costs vary with the number of other tasks one must perform, fatigue, intrinsic interest in the task, and cognitive overhead (see Figure 6).

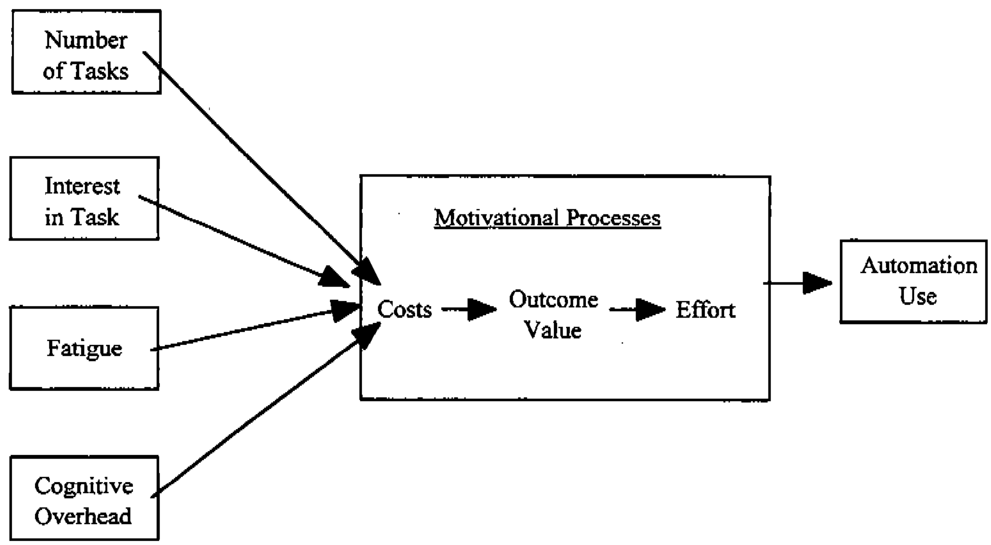

Figure 6. Costs.

3.3.3.1 Number of tasks

As workload increases, the cost of performing a specific task increases, thereby increasing automation use (and the potential for misuse). In Study 2 of Parasuraman and others (1993), misuse did not occur among participants who were required only to perform the automated task. Over-reliance on automation was found only among participants who had to manually perform two additional tasks. Similarly, Thackray and Touchstone (1989b) did not find differences in detection of failures between aided and unaided participants performing a single task. Thus, consistent with the framework, increasing the number of tasks increased the likelihood for misuse.

3.3.3.2 Fatigue

The more fatigued the human operator is, the higher the cost of performing an additional task. Therefore, we would expect automation use to be greater with more fatigued than less fatigued human operators. In some instances, this will lead to appropriate automation use, but in other instances, this will lead to misuse of the automated aid.

3.3.3.3 Interest in the task

The costs of performing a task that is intrinsically interesting are less than the costs of performing a less interesting task. For example, the cost of performing boring, redundant tasks is higher than the cost of performing interesting tasks. If the task is boring enough, the costs might outweigh the importance; outcome

value will be decreased, effort will be lower, and automation use and the potential for misuse will rise.

3.3.3.4 Cognitive overhead

If the cost to change from manual operation to automation use is great, one is less likely to put forth the effort to make the change. Parasuraman and Riley (1997) indicate that high cognitive overhead can induce complacency or misuse if participants initially allocate the task to the automated system. Similarly, high cognitive overhead can induce disuse if participants initially allocate the task to manual operation.

In summary, if the costs of manual operation exceed importance because of a great number of tasks, fatigue of the human operator, boredom of the task, and/or cognitive overhead, then outcome value will be low. The amount of effort expended on the task is predicted to be low. Thus, the likelihood for automation use and the potential for misuse will be great.

Costs will only affect automation use if they are deemed greater than the importance of the outcome. If the importance of the outcome is deemed greater than the cost, outcome value will be high, thereby increasing effort. The likelihood for automation use is low in this situation, making the possibility for disuse potentially large.

Importance is predicted to be affected by the rewards of successful task completion and the penalties of task failure (see Figure 7).

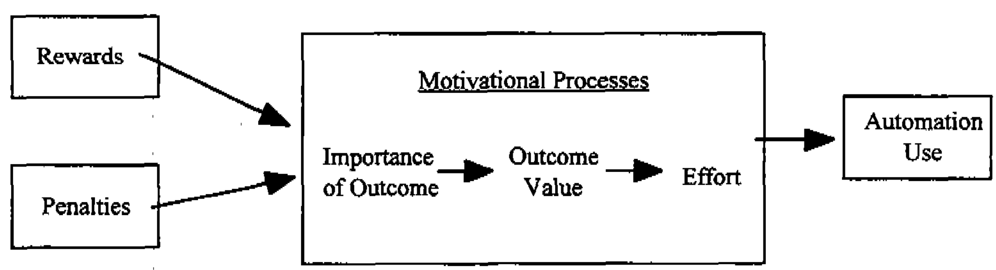

Figure 7. Importance of Outcome.

3.3.3.5 Rewards

When successful completion of the task leads to highly valued resources (e.g., money, prestige), and if the rewards are not outweighed by the costs of succeeding, then outcome value will be high and participants are predicted to work hard. Human operators will not rely on the automated aid; rather, they will put forth the effort to complete the task. Often, this strategy will be appropriate; sometimes, disuse will occur, however.

3.3.3.6 Penalties

Similarly, when grave penalties are a consequence of unsuccessful completion of the task, specifically when the penalties of failure outweigh the costs of succeeding, then outcome value will be high and participants are predicted to work hard. In some situations, this will lead to an optimal task allocation decision; sometimes, it will lead to disuse of automated aids.

On the battlefield, sub-optimal human-computer performance can be lethal; outcome value is extremely high. In combat, disuse may be more of a problem than misuse. Among such highly motivated people, misuse may not exist at all! This is consistent with findings from some interviews with Gulf War soldiers who indicated that they turned off their automated systems.

For this reason, it is imperative that some of the research testing of the model be performed in more combat-like environments. At the very least, researchers should examine automation reliance while varying the consequences for successful task performance. Although it is intuitively appealing, albeit somewhat obvious, to predict that instituting positive consequences for successful performance would lead to improved automation reliance, this may not necessarily occur. In Studies 2 and 3 of Dzindolet and others (1999) and experiments by Moes and others (1999), participants earned coupons or extra credit for correct decisions. Yet, in all three studies, disuse prevailed. Of course, in these studies, the consequences were not varied. We predict that increasing the rewards and/or the penalties for correct decisions would have decreased disuse. Future research needs to determine the validity of such predictions.

In summary, penalties and rewards will affect the importance of successful completion of the task. If importance is greater than costs associated with performing the task, outcome value will be high, leading effort to be expended, and automation use to be less likely. In some situations, this will lead to an optimal task allocation decision; sometimes, it will lead to disuse of automated aids.

In conclusion, the framework of automation use predicts that cognitive, motivational, and social processes work together to cause misuse, disuse, and appropriate automation use. Many factors affect each of the processes and may therefore affect automation use. The reliability of the automated aid, the reliability of manual operation, and several cognitive biases (including self-serving and the bias toward automation) combine to affect the perceived utility of the aid. When the perceived utility of the aid is high, the operator is likely to trust the aid and feel dispensable; his or her efforts are not necessary for the task to be completed. Automation use is predicted to be high through both social and motivational processes. Fatigue, number of tasks, intrinsic interest in the task, cognitive overhead, penalties for task failure, and rewards for task completion combine to affect the outcome value, which also will affect the effort the human

will expend on the task and the likelihood he or she will rely on the automated aid (see Figure 8).

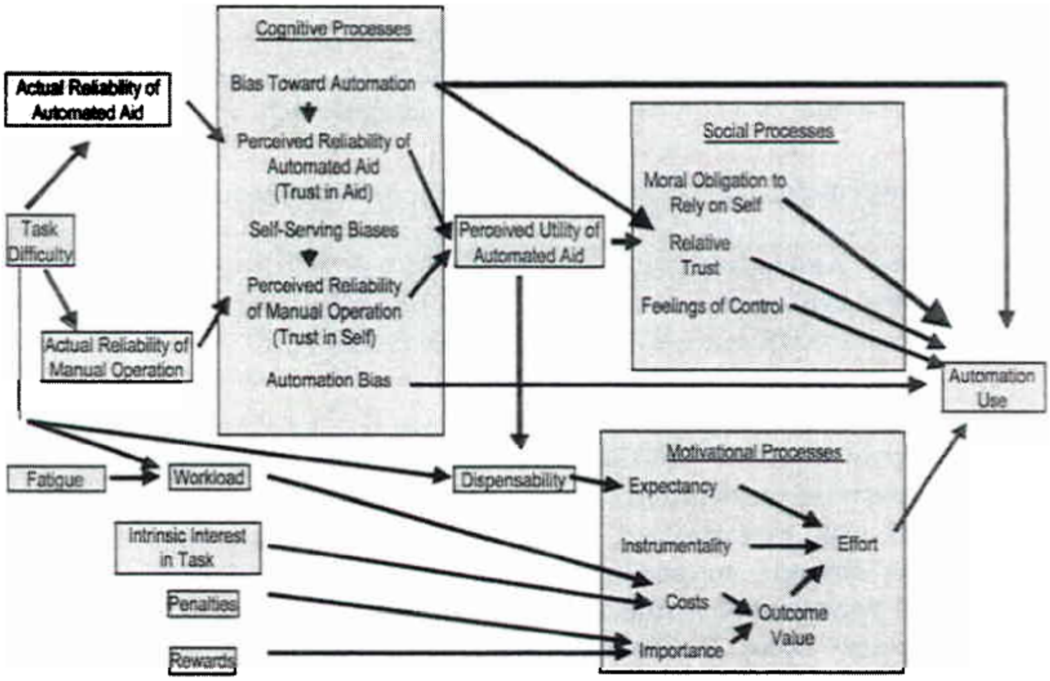

Figure 8. Framework of Automation Use.

Future research needs to determine the effect of each of the cognitive, social, and motivational processes on automation use. To examine one such process, the other two processes will have to be controlled or held constant. Such a procedure was discussed earlier in the report (see pages 4-5) (Studies 2 and 3 by Dzindolet et al., 1999). In both experiments, researchers eliminated the automation bias by providing participants with the automated aid's decision only after the human operator had indicated his or her decision. In addition, motivational processes were controlled. The effort necessary to expend for a self-reliance decision was equivalent to the effort necessary to expend for an automation-reliance decision. Using this procedure, the researchers were able to examine the social processes. Disuse was found to be widespread and difficult to improve.

In addition, the interaction of the three processes must be examined. Specifically, the relative importance of each process needs to be determined. When all three processes were free to impact automation use, Dzindolet and others (to be published) found misuse to be more prevalent than disuse. Would increasing the penalties and rewards for correct decisions reduce the misuse? How high would the consequences have to be before the reduction in misuse became disuse?

Controlling the automation bias and the cognitive processes, Dzindolet and others (1999) found disuse rather than misuse to be prevalent. Ostensibly, the

tendency toward disuse found in these studies was counteracted by the automation bias in the study by Dzindolet and others (to be published) to such an extent that misuse became more of a problem than disuse. How much weight does the automation bias play in automation use? How strong must the disuse due to social processes be to counteract the automation bias?

Clearly, much research is needed to examine this framework. We believe the framework will prove useful to researchers interested in reducing automation misuse and disuse.

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13. ABSTRACT *(Maximum 200 words)*

Although dramatic increases in the use of automation in recent years have occurred across society, research has found that human operators often under-use (disuse) and overly rely on (misuse) automated aids (Parasuraman & Riley, 1997). A general framework of automation use, which proposes that cognitive, social, and motivational processes may lead to productivity loss of human-computer teams, is developed, described, and defended with anecdotal and experimental findings. More specifically, automation use is predicted to be affected by the difference between the reliability of the automated aid and the reliability of manual operation, task difficulty, the number of tasks, interest in the task, fatigue, cognitive overhead, the rewards for successful performance, the penalties for unsuccessful performance, and several cognitive biases. Suggestions for future research are briefly discussed.

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